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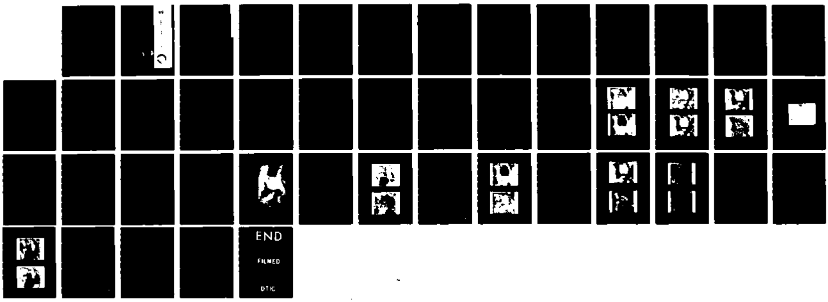

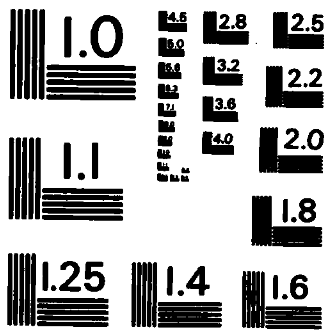
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ETL-0370

AD-A159 220

Texture analysis and cartographic feature extraction

Robert S. Rand

January 1985

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U.S. ARMY CORPS OF ENGINEERS
ENGINEER TOPOGRAPHIC LABORATORIES
FORT BELVOIR, VIRGINIA 22060-5546

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Investigations into using various image descriptors as well as developing interactive feature extraction software on the Digital Image Analysis Laboratory (DIAL) have culminated in a revised procedure to test statistical classification methods. An interactive experiment using this procedure was performed and showed that of the image descriptors tested, the most significant was a two component vector derived from an average and a standard deviation measure of gray shades. The texture measures failed to deliver any increase in performance

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for the classifier. In general this report shows that statistical classification methods are insufficient by themselves to deliver the performance needed in a semi-automated cartographic feature extraction system. Originator-supplied keywords:

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PREFACE

This study was conducted under DA Project 4A762707A855, Task B, Work Unit 0026, "Topographic Mapping Techniques."

The study was done in 1983 under the supervision of Mr. Dale E. Howell, Chief, Information Sciences Division; and Mr. Lawrence A. Gambino, Director, Computer Sciences Laboratory.

COL Edward K. Wintz, CE, was Commander and Director, and Mr. Walter E. Boge was Technical Director of the Engineer Topographic Laboratories during the report preparation.

CONTENTS

ILLUSTRATIONS

TABLES

TEXTURE ANALYSIS AND CARTOGRAPHIC

FEATURE EXTRACTION

INTRODUCTION

Since FY80, semiautomated feature extraction has been studied at the Computer Sciences Laboratory (CSL), Engineer Topographic Laboratories (ETL), as part of the 5-year Army Feature Extraction Plan. The goal of this effort is to provide the Defense Mapping Agency (DMA) with a digital semiautomated feature extraction system that can extract Mapping, Charting, and Geodesy (MC&G) features in DMA's production environment. Thus far, the problem has been simplified to consider only the easiest of cartographic features, such as buildings, roads, forests, fields, and lakes. A variety of approaches have included the study of statistical classification, postprocessing (relaxation and binary image cleansing), lineal detectors, and stereo correlation. This report describes the recent development and evaluation of classification techniques for feature extraction.

Two efforts have contributed significantly to the study of statistical classification techniques at CSL. One of these efforts was a series of experiments on texture and image segmentation, done in-house and discussed in earlier ETL research notes.* This work studied the feasibility of using various image descriptors -- Max-Min texture, edge texture measures, and Ad-Hoc measure, and Laws texture -- in a supervised classification algorithm to identify cartographic features. Data reduction on the descriptors was attempted using the divergence measure and principal components. In addition, attempts were made to reduce misclassification by relaxation and raster-processing techniques.

The second effort was the development of feature extraction software on the Digital Image Analysis Laboratory (DIAL), done under contract with IBM. The software was implemented after an initial task to survey the available feature extraction techniques was completed. Essentially, two methods of classification were selected, a supervised method using the Maximum Likelihood (Bayes) algorithm and an unsupervised (Clustering) method based on the ISODATA algorithm. These methods and a number of associated support and evaluation functions were developed and implemented on DIAL. The resulting interactive system is a research tool invoking a sophisticated work station and color display capability. The system is designed to handle up to 24 channels of

*See the three reports written by Crombie, Rand, and Friend in the bibliography, and a fourth report written by Rand and Shine.

input data, which can come from a variety of sources including panchromatic and infrared imagery, LANDSAT imagery, and texture data. Documentation of the system and its use was published in two volumes.[1,2]

Cleansing methods, which are applied to the output of most any classification process, have undergone a significant development on DIAL. Two approaches have been tested, namely probabilistic relaxation and raster processing.[3,4] The routine for probabilistic relaxation is available on DIAL; however, results thus far have been discouraging because of the many iterations required to achieve significant improvements over an initial classification. Raster processing, which is interfaced with STARAN's associative array processor (and DIAL), has been very successful in achieving good results. However, the drawback to this technique is the reason for its success; raster processing is a very interactive procedure, where all decisions are made by the user.

This research note updates the classification procedure currently available on DIAL and emphasizes its generality in solving classification problems. The update is necessary because although DIAL's software package has been available in the past, supporting routines that generate the image descriptors of interest to CSL had not been written. DIAL was used to classify LANDSAT imagery; whereas, texture analysis and image segmentation work was done off line. However, a number of image descriptors can now be generated and utilized by DIAL. All the data manipulation and processing capabilities available to LANDSATMSS can now be accessed by other data types, such as texture. Both the supervised maximum likelihood algorithm and the unsupervised clustering algorithm can be used in a highly interactive mode. Of particular advantage is the capability for a user to display, as an image (or a supervised set of images), the data he plans to use. Up to three channels can be displayed at one time in pseudocolor and used during operations such as the definition of training areas.

Section one is a brief synopsis of this image classification procedure on DIAL with a special application toward the image descriptors generated by the program TEXLAW. Section two discusses an experiment performed using the DIAL

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[1] W. Rice, J. Shipman, R. Spieler, Interactive Digital Image Processing Investigation prepared for U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0172, December 1978, AD-A076 342.

[2] W. Rice, J. Shipman, R. Spieler, Interactive Digital Image Processing Investigation, Phase II, prepared for U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0221, April 1980, AD-A087 518.

[3] A. Rosenfeld, R. Hummel, S. Zucker, "Scene Labeling by Relaxation Operations," IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-6, June 1976.

[4] N. Friend, Analysis of Interactive Image Cleansing Via Raster-Processing Techniques, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0347, November 1983, AD-A141 772.

software. The experiment tests various combinations of the Ad-Hoc and Laws image descriptor, and it does so under a procedure that has eliminated some of the weaknesses inherent in the earlier experiments. For example, the training regions had been confined to rectangular regions and thus included clutter that was not representative of the classes being defined. The data were tested on two independent algorithms, the supervised and the unsupervised classification algorithms.

Unfortunately, the results of this experiment as well as those of all the earlier experiments show that statistical classification methods, by themselves, are insufficient to satisfy the requirements of a semiautomated cartographic feature extraction system. The only hope for these methods is that they may have some use if used in conjunction with other techniques. Such an effort, that is, to coordinate various feature extraction techniques under a "rule-based" system, has started recently. Initially, methods such as edge and boundary detectors are likely to receive first consideration for implementation under this rule-based system.

THE CURRENT CLASSIFICATION PROCEDURE USING DIAL

Introduction to the DIAL System. The Digital Image Analysis Laboratory (DIAL) is an interactive system that has been used at ETL to research a variety of mapping and photointerpretation techniques. Some of DIAL's capabilities include gray level mapping, magnification, filtering operations, mosaics, warping, scrolling, targeting, image fusion, stereo matching and compilation of elevation data, and perspective viewing. Another capability of DIAL is the feature extraction methodology discussed in this report.

DIAL consists of two work stations connected to a mainframe computer system via a PDP 11/50 minicomputer. Each work station has a command station -- tektronix keyboard with display, two trackballs, and an x-y tablet -- and two color display screens. The tektronix display in each work station is linked to a copying unit, and one of the color displays is linked to a DUNN 631 color camera system. The two work stations also use a CYBER 170 sequential computer and have access to a STARAN associative-array processor. Peripheral units include eight disk drives and four magnetic tape units. The system is outlined in figure 1.

The system software on DIAL is made to support a modular program structure. Typically, a programmer wishing to perform a particular task codes his algorithm as a DIAL program module (PM). Users of DIAL can then call the module from one of the work stations. The PM's are called individually, with any output stored on a DIAL file (or a set of DIAL files). Subsequent calls to this PM or other PM's can use the file and produce other files. Thus, a sequence of PM's can be used to perform a number of small tasks that build on each other, resulting in the completion of some larger task.

Description of the Classification Procedure. The current classification procedure on DIAL can be divided into four major blocks: data preparation, data modeling, classification, and postprocessing. In general, the blocks are performed sequentially with the option to repeat and add more data, if necessary. A diagram of these blocks and the steps within each, along with the supporting software, is shown in figure 2.

Data Preparation. In the data preparation block, the user must acquire or generate multichannel data. A variety of digital-data types can be used, including digitized panchromatic and infrared images, LANDSAT images, and texture data, depending on the application. Up to 24 channels of input can be accommodated, and using a combination of various data is perfectly acceptable as long as the resulting channels are registered. Each channel is a plane of data (such as a component to some texture vector or a band from LANDSAT imagery); therefore, if the available data are stored as vectors, the components must be separated into planes. The only system requirement for the data is that each channel be stored as a DIAL image. Thus, if the data consist of nonintegral numbers -- such as is the case with many texture measures -- the numbers need to be transformed appropriately to be integers so that the data can be made into an image. Once the channels of data are available as registered DIAL images, the final operation in this block is to build a "composite" image. It is this composite image that is used in the computations involved in the Data Modeling and Classification blocks.

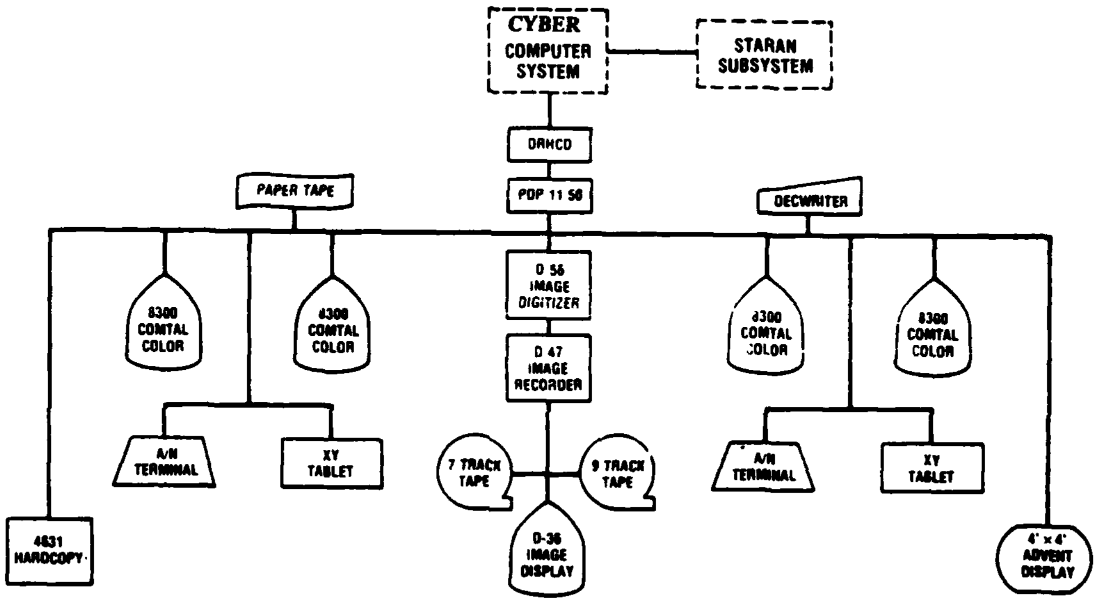

Figure 1. DIAL system.

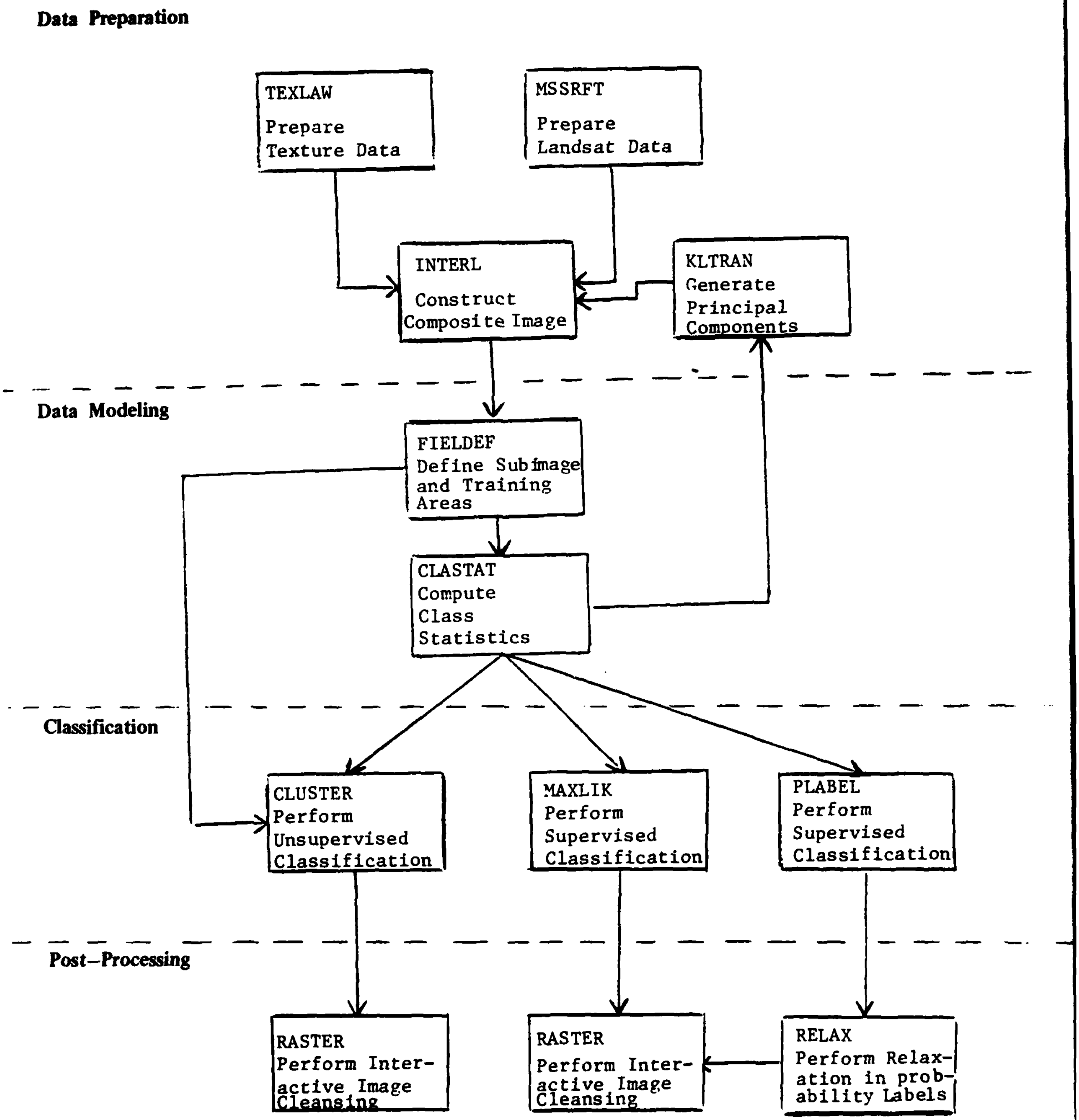

Figure 2. Diagram of classification procedure on DIAL.

There are six PM's that assist the data preparation process: TEXLAW, MSSRFT, RATIOF, INTERL, SAVE, and KLTRAN. The program TEXLAW generates various image descriptors and creates a DIAL image for each component of the descriptor selected. Descriptors include the measures previously studied by CSL, such as the Ad-Hoc measure[5] and Laws texture measure.[6] The program MSSRFT is used when accessing LANDSATMSS data to transform data residing on "computer compatible tapes" (CCT's) thereby creating a set of four DIAL images on disk. Neither TEXLAW nor MSSRFT operate as DIAL PM's; however, they serve the function of preparing data for the remaining programs that do run on DIAL. Therefore, they are included as part of DIAL's feature extraction package. The program RATIOF, as its name suggests, ratios one DIAL image to another; the value of each point in the "numerator" image is divided by the corresponding point in the "denominator" image; its output is a DIAL image of the ratio. The program INTERL interleaves interactively selected images, building a composite image of up to 24 channels in a band-interleaved-by-pixel format. SAVE is used after INTERL and RATIOF to save an image permanently, if desired; it is also used after the program KLTRAN.

The KLTRAN program enables the user to transform a composite image consisting of N channels ($N \leq 24$) into a set of N principal-component images, based on a covariance matrix derived from the composite in the CLASTAT PM. Because the covariance matrix is needed, one must make at least one pass through the Data-Modeling block before using KLTRAN, and then repeat the Data-Preparation block with the principal-component data. In KLTRAN, the covariance matrix is used in a Karhunen-Loeve transformation to create a new composite image consisting of the principal components of the original composite. Since a subset of the principal components is usually desired, the user will typically invoke the option in KLTRAN that separates the desired components into a set of individual DIAL images. At this point, INTERL must be called again to interleave the new subset, followed by a call to SAVE.

Data-Modeling. The data-modeling block establishes the initial conditions and support data needed during classification. This block is implemented via FIELDEF and CLASTAT. The effect of the FIELDEF routine is to create a field/class DIAL file storing the locations of a set of fields (image subareas of interest to the user). The effect of CLASTAT is to extend the file with a set of classes, consisting of statistical models for the fields of interest.

The usage of FIELDEF and CLASTAT varies depending on whether one will later choose to classify the data using the supervised classification routine (MAXLIK) or the unsupervised routine (CLUSTER). If an unsupervised approach is taken and if the starting vectors are self-generated (see the discussion on

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[5] M. Crombie, N. Friend, R. Rand, Feature Component Reduction Through Divergence Analysis, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0305, October 1982, AD-A123 474.

[6] R. Rand and J. Shine, Feature Analysis and Reduction of the Laws Texture Measure, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0343, October 1983, AD-A138 366.

CLUSTER routine on page 10), no training sets need be defined, and only FIELDEF is called to define the subimage for classification; however, if the starting vectors are not self-generated but defined according to the statistics of selected training areas, both FIELDEF and CLASTAT are used in a manner similar to that of taking the supervised approach. As an option, FIELDEF can also be used here to define reference areas to analyze results. That is, if a region (such as a forest area) is outlined, the final results in this area can later be viewed yielding such information as the percentage of points correctly assigned to the cluster (associated with forest).

If the data are classified using the supervised approach, both FIELDEF and CLASTAT are invoked. In this case, FIELDEF is called to define the areas (fields) that will be used by CLASTAT in computing training sets, as well as to define the classification and reference areas. CLASTAT generates the training sets needed by MAXLIK. A training set is a set of class records, each record being a statistical model of a class and consisting of a mean vector and a covariance matrix of an area (field) previously defined in FIELDEF. In addition to their function in the MAXLIK algorithm, the mean vectors in the training sets are also what are used to generate the starting vectors needed in a class-generated clustering approach.

To aid in the selection of training models, CLASTAT can measure the distance between two classes. This measure, called the Bhattacharyya distance, has values ranging between zero and one. A value of one indicates there is no separation between two classes; a value very close to zero indicates good separation. The order of magnitude is what is important. For example, a distance value of 10^{-12} would show good separation; whereas, a value of 10^{-1} would show poor separation. Another criterion to selecting good classes is to check the mean and standard deviation of each channel. Generally, if the standard deviations are high compared to the means, the corresponding area on the image is not homogeneous and the class will not make a good training model.

To obtain the optimum training set, a user may have to switch back and forth between FIELDEF and CLASTAT, taking advantage of the highly interactive nature of each program. Typically, the optimum set will be derived from a set of homogeneous fields that are well separated. The display capability in FIELDEF is particularly useful in selecting the fields, since the characteristics of homogeneity and separability can usually be spotted visually. FIELDEF will superimpose any three of the composites' channels on color overlays. When selecting a field, one uses this capability and with a cursor draws a polygon or line segment of up to 12 vertices. With the exception of the cluster routine, FIELDEF and CLASTAT are by far the most interactive PM's for the DIAL classification package. The user will spend most of his time here.

Classification. In the classification block, the user implements one of two classification routines, using the data derived from blocks one and two. MAXLIK is the DIAL PM that performs the supervised classification; CLUSTER performs the unsupervised classification.

The MAXLIK routine classifies a subimage in the composite image, assigning each point (data vector) to the class with the smallest value of the likelihood function. Essentially, the tasks involve:

1. Selecting a composite image.
2. Selecting fields from a field/class file.
3. Selecting classes from a field/class file.
4. Assigning a color and a character to each class.
5. Selecting the complexity of the discriminator.
6. Assigning a priori weights to classes.
7. Displaying results.

By selecting a set of fields, the user has defined the subimage to be classified as the smallest rectangular area in the image enclosing the set. This subimage can be displayed, if desired. The set of classes selected by the user will be used as the training model to assign labels to each point in the subimage. Up to 10 classes can be chosen. A color is assigned to each class so that the results can be displayed as a color map on one of the monitors. The map is a DIAL image file containing a pseudocolor function memory that can be saved and later redisplayed. An option to assign characters to each class is available so that the results can be viewed in greater detail (point by point) on either the work station screen or the line printer.

The complexity of the discriminator varies depending on the form that the covariance matrix (of the class models) takes in the likelihood function. The user has the option to use the full covariance matrix, the diagonal elements of the covariance matrix, the expected value of the trace of the covariance matrix, or the identity matrix. Except for the full covariance, the other options lead to successively greater approximation in the discriminator (the likelihood function).

$$L_k(x) = \log \left|\Sigma_k\right| + (x-\mu_k)^T \ \Sigma_k^{-1} \ (x-\mu_k) - 2 \log P_k \qquad (1)$$

where

X = data vector for point in question
μ_k = mean vector for the K^{th} class
Σ_k = covariance matrix for the K^{th} class
P_k = a priori weight for the K^{th} class

The greater the approximation, the lesser the number of computations required in the second term. For example, the full covariance contains $K(K+1)/2$ elements, whereas, the diagonal of the covariance contains only K elements; using the identity matrix eliminates the second term entirely. As for assigning values to the a priori weights P_k, the default is to assign equal weights to all the classes. Such a default eliminates the need for the third term, an additional approximation.

Synonymous with MAXLIK is another DIAL PM called PLABEL. Basically, PLABEL is a modified version of MAXLIK that was made so that the results of MAXLIK could be smoothed by a probabilistic relaxation algorithm. The implementation of PLABEL is almost identical with that of MAXLIK, except that the processing time of PLABEL is somewhat longer. Therefore, if one wishes to process the results of MAXLIK with the relaxation algorithm, one should use PLABEL in place of MAXLIK; otherwise one should use MAXLIK.

The CLUSTER routine is an iterative unsupervised classification process based on Ball and Hall's ISODATA (Iterative Self-Organizing Data Analysis Techniques A) algorithm.[7] The algorithm makes multiple passes through the data, assigning data to clusters and splitting or combining clusters in a user-defined sequence. Essentially, the tasks involve:

1. Selecting a composite image.
2. Selecting fields from a field/class file.
3. Selecting cluster parameters.
4. Selecting starting vectors.
5. Performing a cluster sequence.
6. Displaying results.
7. Stopping or going back to task 3 and reiterating.

In completing task 1 and task 2, the user has defined the subimage that will be processed into clusters. As is the case with MAXLIK, this subimage is the smallest rectangular area on the image enclosing the set of fields. The subimage can be displayed on a monitor, if desired. There are 11 initial clustering parameters, along with a split/combine sequence, that must be specified. Such information as thresholds for splitting and combining clusters, scale factors, the distance measure used in combining clusters, the distance measure used in assigning data points to clusters, the minimum number of data points in a cluster, and the maximum number of clusters allowed, is supplied in this task. Since a few of these parameters are sensitive to the characteristics of the data, a certain amount of experimentation might be necessary to obtain optimal results.

Starting vectors are used to specify cluster centers for the initial assignment of data to clusters. There are three methods available:

1. Self-generated, in which the routine selects a single starting vector consisting of zeros in all channels.

2. Class-generated, in which the user selects up to 50 previously defined classes (from a field/class file) as starting vectors.

3. Previously generated, in which the starting vectors are defined as the clusters determined during the immediately preceding cluster run of the present DIAL session.

Of course this third method cannot be exercised until the cluster sequence has been performed at least once. The use of previously generated starting vectors is particularly useful when one wishes to extend the clustering sequence after viewing the displayed results in task 6.

After the cluster parameters, the starting vectors, and the split/combine sequence are defined, it is a simple matter of one command to implement the clustering process. Upon completion of the process, the user can immediately

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[7] W. Rice, J. Shipman, R. Spieler, Interactive Digital Image Processing Investigation, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA. ETL-0172, December 1978, AD-A076 342.

display the resulting class map, since a color code has automatically assigned a color to each cluster. If desired, the user can assign a character to each cluster and make a point-by-point analysis of the results. At this point, if the results are satisfactory, the user may stop. Otherwise, the process can continue by returning to task 3. The clustering can then proceed from scratch or from the previously generated clusters.

Postprocessing. After a scene has been classified, there are two methods available on DIAL for image smoothing: probabilistic relaxation and raster processing. The relaxation method is based on an approach developed by A. Rosenfeld at the University of Maryland.[8] This method considers the influence of a neighborhood on a point, and exploits concepts of information theory to modify a point's existing class label. Each point must have been assigned a set of class labels along with a set of probabilities associated with the labels, rather than one definite class label. As an option, a certain amount of external knowledge about the compatibility of the classes can be embedded into the process using a compatibility matrix. The relaxation function then updates a class label based on the information about the point and its surrounding area, attempting to minimize the entropy of the probability set associated with the point. The formula for updating the probability $p_{ij}^{n}(\lambda_k)$ for the (i,j) point of the Kth class is

$$p_{ij}^{n+1}(\lambda_k) = \frac{p_{ij}^{n}(\lambda_k)\left[1 + q_{ij}^{n}(\lambda_k)\right]}{\sum_{k=1}^{N} p_{ij}^{n}(\lambda_k)\left[1 + q_{ij}^{n}(\lambda_k)\right]} \tag{2}$$

where

$$q_{ij}^{n}(\lambda_k) = \sum_{l,m} C_{ijlm} \sum_{k'} r_{ijlm}(\lambda_k \; \lambda_{k'})\, p_{lm}^{n}(\lambda_{k'})$$

and

n = superscript that indicates the iteration number

$r_{ijlm}(\lambda_k \; \lambda_{k'})$ = the compatibility of label λ_k for the point (i,j) with the label λ_k for point (l,m); takes on values in the interval [-1, 1]

C_{ijlm} = the weighting of the points (l,m) that are neighbors of point (i,j);

$0 < C_{ijlm} \leq 1$ and $\sum_{lm} C_{ijlm} = 1$ for each point (i,j)

$\sum_{K=1}^{N} P_{ij}^{n}(\lambda_k) = 1$ for all pairs (i,j) and all interations N

The DIAL routines for implementing the relaxation process are RELAX and ITRES. RELAX will update the class labels and the associated probability

8 A. Rosenfeld, R. Hummel, S. Zucker, "Scene Labeling by Relaxation Operations," IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-6, June 1976.

estimates. The user interactively selects the values for the compatibility matrix r and weighting (distance) matrix C. RELAX takes the class maps generated from PLABEL as input. Recall that PLABEL is a modified version of MAXLIK designed specifically to generate data for the RELAX routine. ITRES is a displaying routine that presents the results yielded by RELAX.

The second method for image smoothing is the raster-processing approach.[9] The name is derived from the fact that the RASTER PM processes data in a raster format, as opposed to a vector format. The method is subjective since the user is the one who decides what areas are to be retained and what areas are to be erased, and what areas are to be expanded and what areas are to be shrunk. The RASTER PM was written by Goodyear Aerospace Corporation for the STARAN associative array processor, which is ideally suited to processing raster data since the data are generally stored in an array format.

Since RASTER requires binary imagery, the standard procedure for using RASTER in a classification sequence is to establish binary planes of data, one for each class that is identified. These class planes contain values of one or zero; one, if a point is a member of the class and zero, if it is not. The user then interactively cleanses these images via calls to the nine available raster functions.

Program TEXLAW The purpose of TEXLAW is to generate image planes of texture data from single-channel gray shade images. Two texture measures previously studied by ETL, the two-component Ad-Hoc texture measure and the Laws texture measure,[10] can be computed using this routine. In addition, many other texture measures can be constructed using the program's two-step procedure. The resulting texture data are stored as a set of DIAL image planes, each plane corresponding to one texture component, and the set is compatible with the DIAL program modules for classifying multichannel imagery.

A two-step procedure is used to compute the image descriptors. In the first step, an intermediate image is generated by convolving the original image with a symmetric mask defined by the user. In the second step, the intermediate image is operated on with one of three pairs of window functions selected by the user. The purpose of this second step is to produce components that are either low frequency functions (creating a blurring effect) or high frequency functions (energy measures that enhance edges of structural information) of the intermediate image. These various texture measures can be divided into two groups:

TEXTURE MEASURES: GROUP 1

The two-component Ad-Hoc texture measure (average and standard deviation).

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[9]N. Friend, Analysis of Interactive Image Cleansing Via Raster Processing Techniques, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA., ETL-0347, November 1983, AD-A141 772.

[10]K. Laws, Textured Image Segmentation," Image Processing Institute, (USCIPI Report 940), Univ. of Southern California, Los Angeles, CA, January 1980.

The two-component correlation texture measure (magnitude and direction).
The two-component gradient measure (magnitude and direction).

TEXTURE MEASURES: GROUP 2

The Laws texture measure (individual components).
Variations of Laws texture (individual components; the energy measure is replaced by either the correlation or gradient measure).

There are two types of sampling used in TEXLAW. The first type occurs for selecting a regularly spaced grid of points on both the source and the intermediate image and is defined by the sampling factors "SKIP1" and "SKIP2." The effect of this sampling is to reduce the size of the intermediate image and size of the DIAL images. (Example: NPIX = (NP-1)/SKIP1 + 1, where NP is the number of pixels on the source and NPIX is the resulting number of pixels on a record of the intermediate image; and NPIX2 = (NPIX-1)/SKIP2 + 1, where NPIX2 is the resulting number of pixels on a record of the DIAL image.)

The other type of sampling is an option used to reduce the number of computations during the window operation in the second step. If WSZ**2 is the number of points used in the computation and NEXP is the expansion (sampling) factor used to select these points, the effective size of the window covers an area of NWSZ**2, where NWSZ = (WSZ-1)*NEXP + 1. Therefore, large window operations can be simulated at the same cost as performing small window operations. This option was added to enable a user to experiment with the possibility of using large window areas in the texture operation without using the corresponding large number of points.

TEXLAW can be used iteratively. The DIAL images that are generated are filled at the edges so that windowing does not decrease their size. Thus, output images are registered to the input images when SKIP1 = SKIP2 = 1. These outputs can be used as input to another iteration. For example, two images can be created using AVE and STD as a first iteration. Another run can follow this with the input image from STD, using AVE and STD to generate two additional outputs, the first a blur of the STD image and the second an energy measure of the STD image. Thus, higher order texture measures can be computed from lower order measures using an iterative strategy.

AN EXPERIMENT USING DIAL's CLASSIFICATION PROCEDURE

A classification experiment was performed on DIAL following the procedure described in the previous section. The purpose of the experiment was to test some of the more promising image descriptors considered in earlier studies under a more flexible and interactive classification system. Because of a rather rigid classification procedure in the previous studies, the possibility existed that the poor performance of the image descriptors was due not only to their own weaknesses in supplying descriminatory information but also to weaknesses in the classification procedure. If the classification scenario was optimized, perhaps the performance of the descriptors could be improved. In addition, there was the possibility that a combination of the more promising image descriptors would improve performance.

Description of Experiment. The source data in the experiment was a panchromatic image containing 1024 by 1024 pixels and having a ground resolution of 1 meter. The scene, called scene A, is a rural area containing forests, fields, a road, and a few buildings and has been used in all of the previous studies on texture and image segmentation. This scene is shown in figure 3.

The experiment can be thought of as consisting of two parts. In part A, 39 images were generated from program TEXLAW, and from these, the most promising were used in both a supervised (MAXLIK) and unsupervised (CLUSTER) classification run. The emphasis here was on choosing a small set of image components. Selecting the fields and classes was a highly interactive procedure requiring a number of field/class definitions and mergings before obtaining what was judged to be an optimal training model. In part B, principal component images were generated from some of the images created in part A, and the effect of both decreasing and increasing the number of components was tested. Only supervised classification runs were invoked.

Part A. Data preparation (Block 1) was initiated by generating 16 pairs of images from scene A, where each pair -- a convolved image and an energy image -- corresponded to a particular LAWS window (see section on program TEXLAW and the appendix). In addition, 15 ratioed images were generated by ratioing the last 15 energy images to the first energy image using program RATIOF, and the ratioed images corresponded to the 15 texture components defined by Laws. Figures 4 and 5 show the pair of images generated from the LAWS window LL. In the top image, every other point on scene A was convolved with LL (a 5X5 window was used). The bottom image is the result of computing the standard deviation about every point in the convolved image (13X13 window). Figures 6 and 7 show the pair of images generated from the LAWS window EE. The result of using program RATIOF, with the EE energy image as the numerator and the LL energy image as the denominator, is shown in figure 8. For a listing of the 16 LAWS convolution masks along with an explanation of their derivations, see the appendix.

The data preparation was completed by selecting those images that appeared to contain the most discriminatory information and building them into a single composite image. Selecting the images was done visually by displaying each of them on one of the work station's monitors and subjectively choosing those that collectively gave the most discriminating ability to a human observer. Since at this point a human being can outperform the computer in identifying cartographic features, it was assumed that if a person fails, then the computer will certainly fail. The most significant images were those associated with the LL and EE images (particularly LL). Of these, three were selected: the convolved image generated by LL, called A54CONLL; the corresponding energy image, called A54STDLL; and the energy image generated by EE, called A54STDEE. The A designates scene A and 54 designates the exposure number of the image; CON represents convolution and STD represents standard deviation. The three images were built into a composite using program INTERL.

Figure 3. Scene A.

Figure 4. Convolved image using LL window.

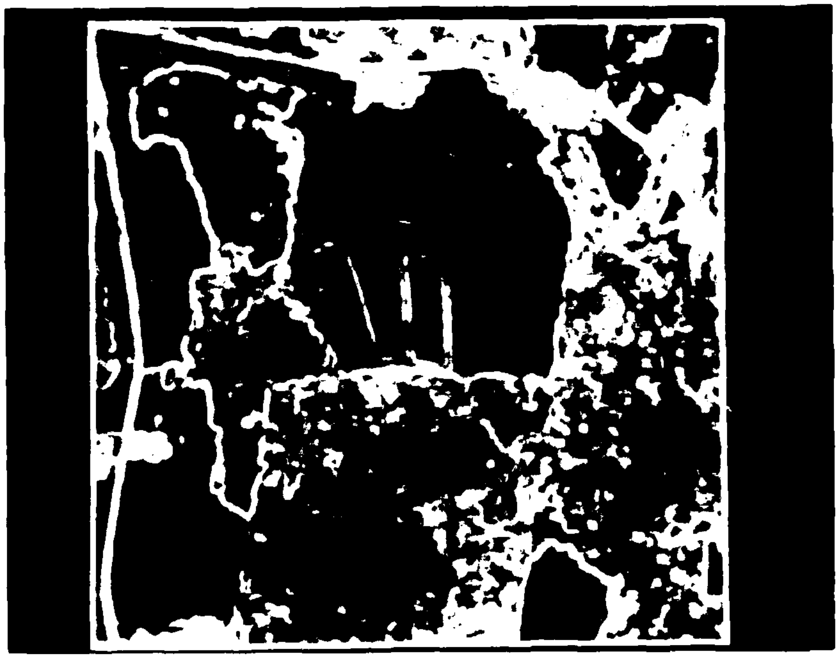

Figure 5. Energy image using LL window.

Figure 6. Convolved image using EE window.

Figure 7. Energy image using EE window.

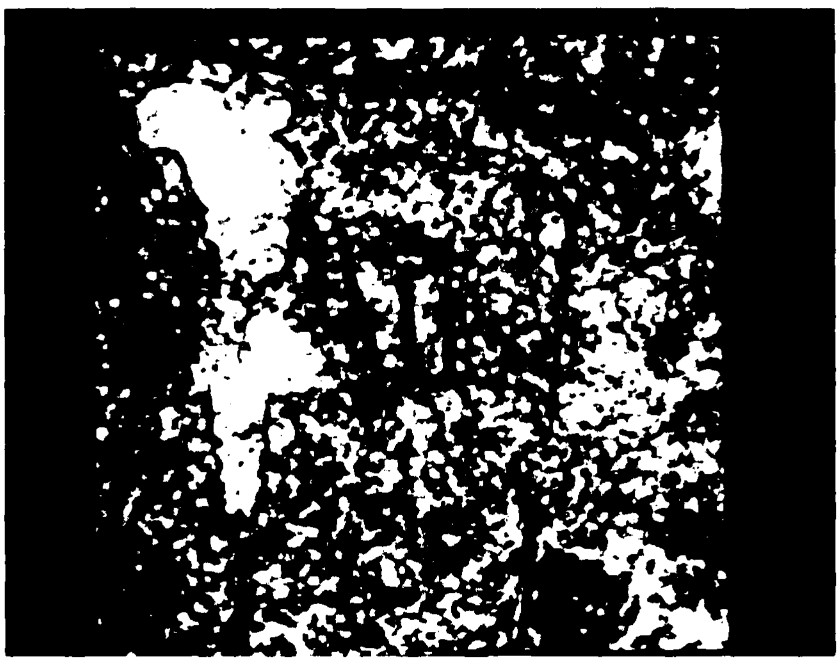

Figure 8. Ratioed image of EE/LL energy images.

The Data Modeling (block 2) was initiated by calling the program FIELDEF, and superimposing A54CONLL, A54STDLL, and A54STDEE on three color planes. This superimposed set is displayed as a false-color image, in which the intensity of each plane can be adjusted to emphasize important features. Regions in the scene that were thought to be of use in the training model were outlined with a cursor using a trackball. A number of polygons were drawn around forest, field, and building areas. Some line segments were drawn along the road in the scene. Table 1 shows a complete list of the fields that were later used to construct the class models. Note the numbers in the middle column that depict the vertices of the polygons or line segments. Note also that, in addition to the small fields, a large field "BASEIMAGE" was defined. This large field defined the area on the scene that was to be classified; essentially the entire image. Figure 9 shows these fields overlayed on top of the false-color image.

Figure 9. False-color display of image components.

Having collected a set of fields to work from, the operator called on CLASTAT to construct the training classes. The process was iterative, where classes were created, and then using the Bhattacharyya distance measure were tested for separability. Table 2 lists the resulting classes. Initially, eight classes were created.

1. The class FOREST 1 from the field HEAVYFOREST.
2. The class FOREST 2 from the fields LIGHTFOREST 1, LIGHTFOREST 2, LIGHTFOREST 1B.
3. The class FOREST 3 from the field LIGHTFOREST 1A
4. The class FIELD 1 from the field FIELD 1
5. The class FIELD 2 from the fields ROUGHFIELD, ROUGHFIELD 1
6. The class ROAD from the field ROADFIELD
7. The class BUILDING from the field BUILDING 1
8. The class SHADOW from the field SHADOW 1

Table 1. Listing of Field Results

SELECT FIELD(S)

SELECTED LINE NO.	FIELD NAME		L1/P1	L2/P2	L3/P3	L4/P4	L5/P5	L6/P6	L7/P7	L8/P8	L9/P9	L10/P10	L11/P11	L12/P12	L13/P13	DESCRIPTION	AREAL LINEAR	NUMBER OF PIXELS	LINE NO.
1.	HEAVYFOREST	LINE	104	102	145	144										HEAVY FOREST FIELS	AREAL	1290	1.
		PIXEL	102	134	136	108													
2.	LIGHTFOREST1	LINE	352	353	364	371	380	381								LIGHT FOREST FIED NO.1	AREAL	386	2.
		PIXEL	170	184	185	178	179	168											
3.	LIGHTFOREST2	LINE	283	288	307	299	302									LIGHT FOREST FIELD NO.2	AREAL	499	3.
		PIXEL	387	415	416	400	386												
4.	FIELD1	LINE	143	143	173	173										FIELD FIELD NO.1	AREAL	1426	4.
		PIXEL	306	352	352	308													
5.	ROUGHFIELD	LINE	213	213	248	248										ROUGH FIELD IN CENTER	AREAL	594	5.
		PIXEL	260	277	278	264													
6.	ROUGHFIELD1	LINE	208	207	241	245										ROUGH FIELD	AREAL	641	6.
		PIXEL	221	238	244	228													
7.	ROADFIELD	LINE	178	233												ROAD FIELD	LINEAR	64	7.
		PIXEL	27	35															
8.	LIGHTFOREST1A	LINE	341	344	375	372	385	384								LIGHT FOREST AREA	AREAL	1947	8.
		PIXEL	249	307	307	280	273	258											
9.	LIGHTFOREST1B	LINE	208	210	237	246	240									LIGHT FOREST AREA	AREAL	1172	9.
		PIXEL	394	425	429	405	392												
10.	BUILDING1	LINE	49	47	49	58	56	59								BUILDING AREA	AREAL	273	10.
		PIXEL	221	235	250	248	236	222											
11.	SHADOW1	LINE	349	350	356											SHADOW AREA	AREAL	40	11.
		PIXEL	33	42	32														
12.	BASEIMAGE	LINE	10	9	504	503										BASE IMAGE FIELD TO CLASSIFY	AREAL	245273	12.
		PIXEL	7	503	503	8													

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Table 2. Listing of Class Results for Three Components

SELECT CLASS(ES)

SELECTED	LINE NO.	CLASS NAME	DESCRIPTION	NUM. OF CHANNELS	NUMBER OF PIXELS	LINE NO.
	1.	FOREST1	FOREST 1 3COMP	3	1290	1.
	2.	FOREST2	FOREST 2 3COMP	3	2057	2.
	3.	FOREST3	FOREST 3 3COMP	3	1947	3.
	4.	FIELD1	FIELD 1 3COMP	3	1426	4.
	5.	FIELD2	FIELD 2 3COMP	3	1235	5.
	6.	ROAD1	ROAD 1 3COMP	3	64	6.

	LINE NO. 1		LINE NO. 2		LINE NO. 3		LINE NO. 4		LINE NO. 5		LINE NO. 6	
CH	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV
1	56.66	5.78	107.88	13.78	131.72	6.08	156.41	4.45	127.12	3.43	216.70	4.73
2	113.14	12.48	139.43	19.24	104.31	10.59	82.99	4.88	93.55	8.59	186.81	5.95
3	174.37	35.07	164.03	34.68	118.29	25.40	89.99	15.47	110.40	20.90	68.91	18.70

SELECT CLASS(ES)

SELECTED	LINE NO.	CLASS NAME	DESCRIPTION	NUM. OF CHANNELS	NUMBER OF PIXELS	LINE NO.
	7.	BUILDING	BUILDING 1 3COMP	3	273	7.
	8.	SHADOW	SHADOW 1 3COMP	3	40	8.
*	9.	FSTFIELD	COMBINED FOREST3 AND FIELD2	3	3182	9.
*	10.	HFOREST	HEAVY FOREST CLASS	3	1290	10.
*	11.	FIELD	FIELD CLASS 3 COMP	3	1426	11.
*	12.	BLGROAD	COMBINED BUILDING ROAD	3	337	12.

	LINE NO. 7		LINE NO. 8		LINE NO. 9		LINE NO. 10		LINE NO. 11		LINE NO. 12	
CH	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV
1	233.85	28.08	98.28	26.87	129.93	5.68	56.66	5.78	156.41	4.45	230.59	26.22
2	184.25	17.56	173.23	31.35	100.13	11.17	113.14	12.48	82.99	4.88	184.74	16.04
3	153.53	53.75	106.80	11.89	115.22	24.06	174.37	35.07	89.99	15.47	137.46	59.24

One can see from the Bhattacharyya distance measures listed in table 3 that some of these training classes were almost inseparable. Classes 2, 3, and 5 had a distance of 10^{-1} or greater; likewise for classes 6 and 7. Also class 8, corresponding to the shadow areas surrounding buildings, had a distance of 10^{-1} between class 1 and class 2. Thus, the following merger and redefinition took place:

> Class 10 (HFOREST) was renamed from class 1.
> Class 11 (FIELD) was renamed from class 4.
> Class 9 (FSTFIELD) was constructed by merging classes 3 and 5.
> Class 12 (BLGROAD) was constructed by merging classes 6 and 7.

The shadow class was dropped from consideration, since a merger of this class with class 1 and/or class 2 would probably lead to greater confusion between these two classes; the separation between class 1 and class 2 was not that good anyway.

Using the set of fields and classes gathered thus far, the classification of scene A (step 3) was performed twice via MAXLIK and CLUSTER. Implementing the MAXLIK PM was straightforward. The field BASEIMAGE, was selected to define the area of classification and classes 9, 10, 11, and 12--depicted by stars to the left of the class names in table 2--were used as a training model. Colors to be associated with classes 9, 10, 11, and 12 were chosen as yellow, blue, green, and red, respectively. The standard Bayes classifier (no approximations) was invoked. Figure 10 shows the results of the classification as a class map, and table 4 shows a table of point-by-point results of the upper left corner of the scene.

The implementation of CLUSTER was less straightforward, requiring much experimentation to determine the best clustering strategy and the most effective parameter values. Until a strategy could be found, small areas of the scene were processed to save time and cost. After a few trials, the "class-generated" approach to selecting starting vectors was found to be the most reliable and accurate. Considering that the classes had already been defined, this approach was also quicker and easier. After adjusting the values of some of the cluster parameters and defining a simple split/combine sequence, the complete scene (defined by the field BASEIMAGE) was classified. Table 5 shows the values of the starting vectors (the same values as the mean vectors for classes 9 through 12, listed in table 2), the clustering parameters, the interim class statistics, and the final cluster population. Although the clustering parameters were discussed only briefly in the previous section, a complete description can be found in Rice, Shipman, and Spieler.[11] However, note that the parameter NVMMAX has limited the maximum number of clusters to four and that a large value of R2 has forced most of the points away from the null cluster and into one of the four clusters (for small values of R2 most points would be assigned into the null cluster). Also the split/combine sequence was defined very simply as one split. The final results of the clustering are shown as a class map in figure 11.

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[11] W. Rice, J. Shipman, R. Spieler, Interactive Digital Image Processing Investigation prepared for U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0172, December 1978, AD-A076 342.

Table 3. Bhattacharyya Distance Measures

Class	1	2	3	4	5	6	7	8
1	*	2	10	23	13	3	6	1
2	2	*	1	3	0	9	2	1
3	10	1	*	2	0	22	4	2
4	23	3	2	*	3	36	5	4
5	13	0	0	3	*	37	4	2
6	3	9	22	36	37	*	1	4
7	6	2	4	5	4	1	*	2
8	1	1	2	4	2	4	2	*

Class	10	11	9	12
10	*	23	10	7
11	23	*	2	6
9	10	2	*	5
12	7	6	5	*

Note: Using a matrix format, the table gives the Bhattacharyya distance between classes, where the values listed are negative powers of ten. For example, the distance between Class 4 and Class 6 in the first table is 1.0×10^{-36}.

Table 4. Subarea of MAXLIK's Class Map Results

```
                                   CLASS CLUSTER MAP RESULTS          CHARACTER FOR-FSTFIELD    S
COMPOSITE IMAGE-----A54LAW3COMP
RESULTS IMAGE NAME  LAWEXP1                                           CHARACTER FOR-HFOREST     H

  PI. MIN     7  PIX MAX    503  LINE MIN      9  LINE MAX    504     CHARACTER FOR-FIELD       F
THRESHOLD =   0.0000
                                                                      CHARACTER FOR-BLGROAD     B
 LINE                               PIXEL
           1         11        21        31        41        51        61        71        81        91
        I---------I---------I---------I---------I---------I---------I---------I---------I---------I----------
    2---BFFBBBBBBFFBBBBBFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBFBFFFFFFFFFFFFFFFFFFFFFFF
    3---BFBBBBBBBFFFBBBBFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBFFFFFFFFFFFFFFFFFFFFFF
    4---BFBBBBBBBFFBBBBBFBBBFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBFFFBFFFFFFFFFFF
    5---BFBBBBBBBFFFFBBFFBBBFFFFFFFFFFBBFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBFFFF
    6---BFBBBBBBBFFFFFFFFFBBBBBFFFFFFFFFFFFFFFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBFFFF
    7---SFBBBBBBBFFFFBBBBBBBBBBBBBFFFFFFFFFFFFFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBFF
    8---BFFBBBBBBFFFBBBBBBBBBBBBBFFFFFFFFFFFFFFFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBB
    9---BFFBBBBBBFFFFBBBBBBBBBBBBFFFFFFFFFFFFFFFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBB
   10---BFFFBBBFFFFFFBBBBBBBBBBBFFFFFFFFFFFFFFFFFFFFFFFRBBBBBBFFFFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBB
   11---BFFFFFFFFFFFFBBBBBBBBBBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBB
   12---BBFFFFFFFFBFFBBBBBBBBBBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFSSSSSSSSSSSFSBBBBBBBBBBBBBBBBBBBBBBBBBBBBB
   13---BBFFFFFFFFBFFBBBBBBBBBBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFSSSSBBBSSSSSSSSSBBBBBBBBBBBBBBBBBBBBBBBBBB
   14---BBFFFFFFFFFFFBBBBBBFFBBBBBBFFFFFFBFFFFFFFFFFFFFFFFFFFFFFBBSSSSSSSSSSSSSSSSSSFFFSSSSBBBBBBBBBBBBBBBBB
   15---BBFFFFFBBBFFBBBBBBBFFBBBBBBBBBBFFFFFFFFFFFFFFFFFFBBBSSBSSSSSSSSSSSSSSSSSSSFFFFFSSSFFSBBBBBBBBBBBBBBB
   16---BBFFBFBBBBFFBBBFFFFFFBBBBBBBBBFFFFFFFFFFFFFFFFFFBBBSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFSSSSSBBBBBBBBBB
   17---BBFFBBBBBBFBBBFFFFFFFBBBBBBBBBBFFBFFFFFFFFFFFFFBBBBSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFSSSSSSSSSSSSSBBB
   18---BBBFBBBBBBFFBBBFFFFFFFFBBBBBBBFFBFFFFFFFFFFFFFBBBBBBSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFSSSSSSSSSSSSSS
   19---BBBFBBBBBBFFBBBFFFFFFFFBBBBBBBBBBBBFFFFFFFFFFFBBBBBBSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFSSSSSSSSSSSSSS
   20---BBBBBBBBBBBBFFFBBFFFFFFFBBBBBBBBBBBFFFFFFFFFFFBBBBBSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFFSSSSSSSSSSSSS
   21---BBBBBBBBBBBBFFFFFFFFFFFFFFBBBBBBBBBBFFFFFFFFFFBBBBSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFFFFSSSSSSSSSSSS
   22---BBBBBBBBBBBBBBBFFFFFFFFFFFFFFBBBBBBBBFBBBFFFFBBBBBSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFFFFFFSSSSSSSSSS
   23---BBBBBBBBBBBBBBBFFFFFFFFFFFFFFFFBBBBBBBFFFFFFBBBBBSSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFFFFFFFSSSSSSSSS
   24---BBBBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFBBBFFFFFBBBBSSSSSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFFFFFSSSSSSSSS
   25---BBBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFSSSSSSSSSSSSSSSSSSSSSSSSSSSSSSSFFFFFFFFFFFFFFSSSSSSSSS
   26---BBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFSSSSSSSSSSSSSSSSSSSBBBBSSSSSSSSSSSFFFFFFFFFFFFFSSSSSSSS
   27---BBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFSSBSSSSSSSSSSSSSSSSSSBBBBSSSSSSSSSSSFFFFFFFFFFFFSSSSSSS
   28---BBBFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFSSBBBBSSSSSSSSSSBBBBBBBBBSSSSSSSSSSSSSSFFFFFFFFFFSSSSSS
   29---BBBFFFFFFFFFFFFFFFBBBBBBBBBBBBFFFFFFFFFFFFFFFFFBBSSSSSSSSSSSBBBBBBBBBBBBBBBBBBBBBBBBBSSSSSSSFFFSSSSS
   30---BBBFFFFFFFFFFFFFBBBBBBBBBBBBBBBSSSFFFFFFFFFFFFFBBBBSSSSSSSSSBBBBBBBBBBBBBBBBBBBBBBBBBBBBBSSSSSSSSSSS
   31---BBBFFFFFFFFFFFFBBBBBBBBBBBBBBBBSSSFFFFFFFFFFFFFBBBBBBBBSSSSBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBSSSSSSSS
   32---BBBBFFFFFFFFFFFBBBBBBBBBBBBBBBBSSSFFFFFFFFFFFFBBBBBBBBBSBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBBSSS
   33---BBBBFFFFFFFFFFFSBBBBBSSSSSSSSSSSSSFFFFFFFFFBBBBBBBBBBBBBBBBBBHHHHHHHHHBSSBBBBHHHBBBBBBBBBBBBBBBBBBSS
   34---BBBBBFFFFFFFFFFSSSSSSSSSSSSSSSSSSSFFFFFFBBBBBBBBBBBBBBBBBBBBHHHHHHHHHHHHHHHHHHHHHHHBBBBBBBBBBBBBBBBB
   35---BBBBBFFBBFFFFFFSSSSSSSSSSSSSSSSSSSSSFFFFBBBBBBBBBBBBBBBBBBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHBBBBBBBBBB
   36---BBBBBBFBBBFFFFFBBSSSSSSSSSSSSSSSSSSSSFFBBBBBBBBBBBBBBHBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHBBBBBBB
   37---BBBBBFFFFFFFFFFSSSSSSSSSSSSSSSSSSSSSSSSBBBBBBBBBBBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHBBB
   38---BBBBBFFFFFFFFFFFFSSSSSSSSSSSSSSSSSSSSSBBBBBBBBBBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHBB
   39---BBBBBFFBFFFFFFFFFFSSSSSSSSSSSSSSSSSSBBBBBBBBBBHHHHHHHHHHHHHBBBBBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHH
   40---BBBBBFBBBFFFFBBBSSSSSSSSSSSSSSSSSSSSSBBBBBBBBHHHHHHHHHHHHHBBBBBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHH
   41---BBBBBFBBBBFFFBBBBSSSSSSSSSSSSSSSSSSSSBBBBBBHHHHHHHHHHHHHHHBBBBBHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHHH
```

Table 5. Listing of Cluster Results

STARTING VECTORS (CLUSTER CENTERS)

CHANNEL	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4
1	129.93	56.66	156.41	230.59
2	100.13	113.14	82.99	184.74
3	115.22	174.37	89.99	137.46

THE CURRENT VALUES OF THE INITIAL CLUSTERING PARAMETERS ARE

1. T1 = 4.5
2. T2 = 3.2
3. NMIN = 30
4. NUMMAX = 4
5. SEP = 1.0
6. ISODAT = 1
7. IDISF = 2
8. P = 0.0
9. R2 = 200.
10. PMAX = 10
11. PN = 1
12. SPLIT/COMBINE SEQUENCE = S

INTERIM CLUSTER STATISTICS

	CLUSTER 1		CLUSTER 2		CLUSTER 3		CLUSTER 4	
CHANNEL	MEAN	ST.DEV	MEAN	ST.DEV	MEAN	ST.DEV	MEAN	ST.DEV
1	129.73	22.68	77.86	22.78	168.19	17.38	169.52	35.51
2	124.39	26.50	138.77	28.70	95.30	19.07	183.24	14.25
3	125.96	23.50	167.78	32.52	86.41	17.61	136.09	48.10

INTERIM CLUSTER STATISTICS

	CLUSTER 1		CLUSTER 2		CLUSTER 3		CLUSTER 4	
CHANNEL	MEAN	ST.DEV	MEAN	ST.DEV	MEAN	ST.DEV	MEAN	ST.DEV
1	122.69	26.62	80.20	22.93	163.96	20.78	155.02	35.51
2	120.14	19.38	141.14	27.42	94.72	15.15	182.26	13.97
3	127.01	21.12	169.42	30.89	89.51	19.48	135.71	44.51

MINPOP (PN+NCHAN) = 4
NO. OF CLUSTERS = 4

CLUSTER POPULATIONS

CLUSTER	POPULATION
1	66726
2	70153
3	82243
4	27312

Figure 10. Class map results using MAXLIK (three components).

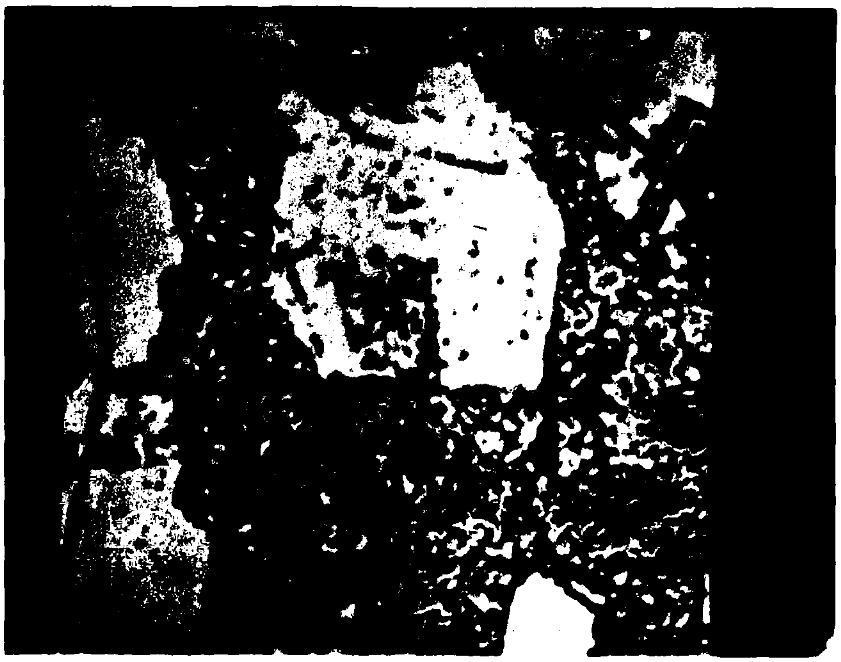

Figure 11. Class map results using CLUSTER (three components).

Table 6. Statistical Parameters of Principal Components

ENHANCEMENT OPTION 3 IMAGE A54PRINC3

BAND	MEAN	VARIANCE	EIGEN VALUES	FRACTION OF TOTAL VAR.
1	125.58	1788.0	3024.0	.22972
2	135.53	3821.6	1100.8	.49101
3	130.61	2173.6	568.13	.27926

ENHANCEMENT OPTION 3 IMAGE A54PRINC8

BAND	MEAN	VARIANCE	EIGEN VALUES	FRACTION OF TOTAL VAR.
1	125.19	1317.9	6578.5	.10373
2	139.56	1120.1	2446.8	.88157E-01
3	137.07	2026.0	946.26	.15945
4	128.78	1607.4	757.03	.12651
5	132.68	1544.1	609.22	.12193
6	120.71	1181.5	544.81	.92938E-01
7	122.79	1056.5	282.57	.83155E-01
8	142.42	2852.1	143.58	.22447

Part B of the experiment used principal component images derived from a selected number of the images already generated by program TEXLAW in part A. Two trials were made; one decreased the number of components, whereas, the other increased the number. In the first trial, the three components used in part A were transformed into principal components, and then a composite image consisting of the two most significant ones was classified by the supervised algorithm MAXLIK. The image's covariance matrix, needed by the KLTRAN PM to perform the transformation, was computed from the statistics of the points within the field BASEIMAGE (enclosing the entire image) using CLASTAT. A call to KLTRAN then produced three principal components, and using one of the PM's options, two DIAL image planes were extracted. Table 6 gives a listing of the statistical parameters associated with the resulting components (see listing under the heading of A54PRINC3). Components one and two were built into a composite image; the DIAL planes are shown in figures 12 and 13.

After the construction of a composite image, the procedure of this first trial followed the steps described in part A. The classes were created using the same fields as those that had created classes 9 through 12, but with the new data in the two-component composite image. Table 7 lists the statistics of the resulting classes. Finally, the last step was taken, i.e. the composite image was processed by MAXLIK invoking the standard classifier. The resulting class map is shown in figure 18.

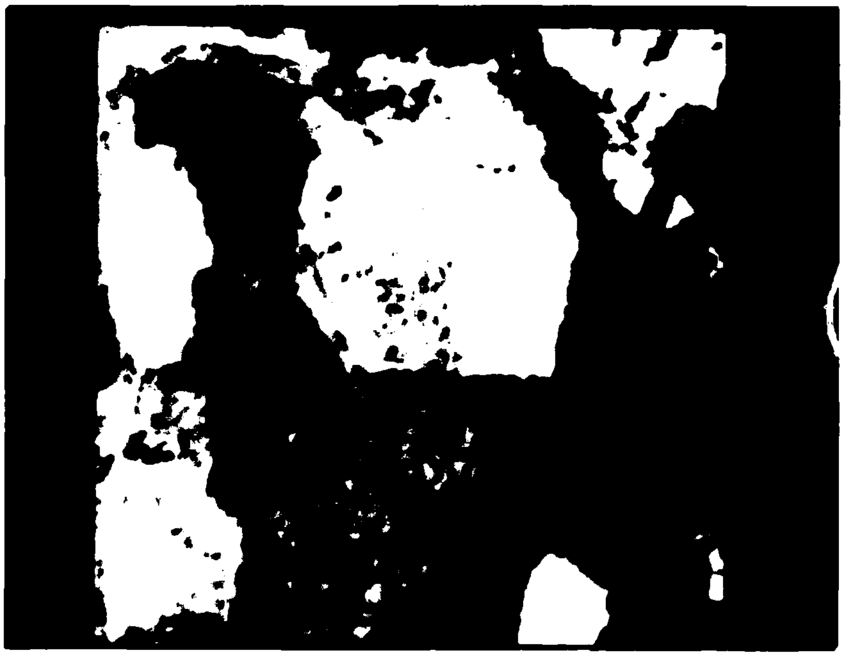

Figure 12. Principal component image (first of three components).

Figure 13. Principal component image (second of three components).

In the second trial, eight of the images generated by TEXLAW in part A were transformed into principal components and the results built into an eight-component composite image. The source images were the three used above, plus an additional five corresponding to the energy components of the LE, LS, LR, EL, and ES Laws windows. The covariance matrix of the source composite image was computed via CLASTAT. Then, using KLTRAN, followed by INTERL, an eight-component composite image consisting of principal components was created. The images of the first, second, fifth, and eighth principal components are shown in figures 14 through 17, respectively; these were the most interesting of the set. The classes were created the same way as in the first trial and their statistics are listed in table 7. The scene was classified twice. In the first, the standard Bayes classifier was invoked, whereas in the second, an approximation to the classifier that only considered the diagonal components of the covariances was invoked. The class map results from the approximated Bayes classifier are shown in figure 19.

Discussion of Results. Surprisingly, the extra step of performing an energy operation over a convolved image added little to the appearance of a derived scene. Comparing the set of convolved images derived from scene A with the corresponding set of energy images shows that except for the convolved/energy pair associated with the LL window there was little visual difference between the sets. The type of similarity that is observed between the pair in figures 6 and 7 also exists in all the pairs except for the LL pair. Thus, in screening out components from the experiment, one can eliminate either the convolved image set or the energy image set without sacrificing information. Except for the LL image, the convolved image set was eliminated because of the desire to test the Laws texture measure, essentially contained within the energy components. However, the convolved image set would probably have yielded equivalent results and was a simpler and less expensive measure.

The set of ratioed images tended to inherit an undesirable property of blacking and whiting out many areas (see figure 8). This property could have been eliminated by adjusting the thresholds used in quantizing the ratioed data. However, since these images really didn't seem to offer anything over the energy components, they were eliminated from further study. Thus, out of the 47 derived images, 17 images remained.

Note that the convolved image using the LL window is a blurred version of scene A, and the corresponding energy image is equivalent to performing a standard deviation operation over the image (see figures 4 and 5). Therefore, this pair of images is synonymous with the Ad-Hoc components studied in one of CSL's previous reports.[12] From a visual inspection of the remaining images, the LL image pair was found to be the most significant. What was disappointing was that none of the other images, except for perhaps the EE energy image, seemed to yield any additional discriminatory information. The majority of them were mostly noise and any information that did exist seemed to already exist on the LL image. Of course, this judgment was made subjectively on a visual basis; what was needed was some quantitative testing.

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[12] M. Crombie, N. Friend and R. Rand, Feature Component Reduction Through Divergence Analysis, U.S. Army Engineer Topographic Laboratories, Fort Belvoir VA, ETL-0305, October 1982, AD-A123 474.

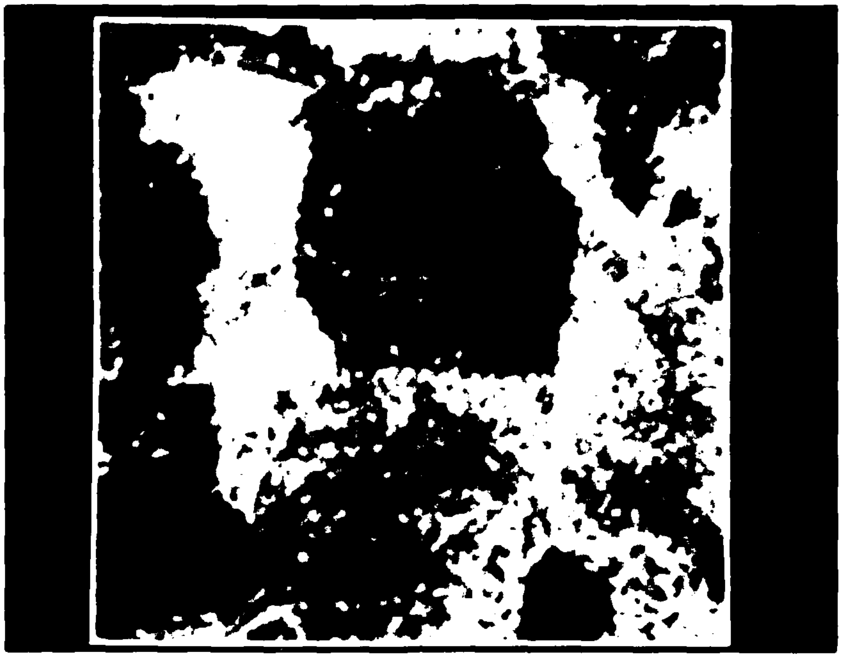

Figure 14. Principal component image (first of eight components).

Figure 15. Principal component image (second of eight components).

Figure 16. Principal component image (fifth of eight components).

Figure 17. Principal component image (eighth of eight components).

Table 7. Listing of class results for principal components

SELECT CLASS(ES)

SELECTED LINE NO.	CLASS NAME	DESCRIPTION	NUM. OF CHANNELS	NUMBER OF PIXELS	LINE NO.
13.	BASE3	STATS OF 3 CH BASE	3	245273	13.
14.	HFOREST2P	HEAVY FOREST 2 PRINC COMP	2	1290	14.
15.	FSTFIELD2P	FOREST,FIELD 2 PRINC COMPONENTS	2	5239	15.
16.	FIELD2P	FIELD 2 PRINCIPAL COMPONENTS	2	1426	16.
17.	BLDROAD2P	BUILDING ROAD 2 PRINCIPAL COMPONENTS	2	337	17.

	LINE NO. 13		LINE NO. 14		LINE NO. 15		LINE NO. 16		LINE NO. 17	
CH	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV	MEAN	STD-DEV
1	127.95	42.41	70.35	19.81	122.53	28.58	172.03	8.58	156.09	35.71
2	124.49	34.10	71.39	19.35	115.14	26.49	100.72	8.21	248.71	11.81
3	127.53	41.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Essentially, the trials of part A and part B tested various combinations of the Laws texture components with the two-component Ad-Hoc image descriptor. In part A, the EE Laws component was added to the Ad-Hoc descriptor and the resulting composite image was classified by both the MAXLIK PM and the CLUSTER PM. Here, neither one of the classification outputs showed an advantage over the other. Considering the increased sophistication of the classification procedure over that of previous efforts, plus the addition of a component, the results of part A were disappointing. The confusion between classes found in the previous study on the Ad-Hoc measure still existed in the new results; in fact, the four-class experiment done with one component (extracted from a 3X3 window) in the previous study did as well as the trial in part A (see figure 5B, ETL-0305[13]).

In part B, the use of principal components had no advantage over the original components. During the run that tested two (out of three) principal components, the building/road class had fewer false alarms along boundaries and in some field areas; however, the hit rate (number of correct hits) remained about the same. The forest and field classes had a lower hit rate (see figure 18).

Surprisingly, the run that tested eight components did no better than the trial in part A that used only three components.

As expected, the quantitative results of part A and part B verified the subjective evaluation made at the beginning of the experiment; the lack of information noticed during the visual inspection of the images materialized in the distance measures computed by CLASTAT and the classification results of MAXLIK and CLUSTER. Thus, the capability to display descriptor data as an image gives the user an excellent means to screen data. There is no need to go through tedious data analysis when a quick and easy display of an image component shows that component to be predominantly noise. Such a display capability is very suitable to an interactive/semiautomated system of feature extraction.

The capability to display image descriptors also provides a good way to explain why points were misclassified. A comparison of figures 4, 5, and 7 (images of the three descriptors) with the class map in figure 10 or figure 11 explains much of what went wrong in that classification. For example, the confusion between the light area at the bottom right of the image and the building/road class is due to the strong similarity between the corresponding areas for the images of figures 4 and 7. Also, the reason for the difficulty in creating separate classes for buildings and roads is easily seen. The difference between these two classes is not in the statistics of the data, but rather in structural information not incorporated into the algorithm. The Laws texture measure was intended to encode such structural information, but this attempt failed. The reason is that the measure is not robust; if the window operators could be tuned to the size of a feature, then structural information might be detected. However, this is impossible without ancillary data about the image and a knowledge-base defining the characteristics of the feature.

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[13] M. Crombie, N. Friend and R. Rand, Feature Component Reduction Through Divergence Analysis, U.S. Army Engineer Topographic Laboratories, Fort Belvoir VA, ETL-0305, October 1982, AD-A123 474.

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Figure 18. Class map results using MAXLIK (two principal components).

Figure 19. Class map results using MAXLIK (eight principal components).

CONCLUSIONS

1. The DIAL system has the capability to use derived image data from operations such as convolutions and texture in an interactive statistical classification process.

2. The capability to display derived data as images is an excellent means of screening. Components that lack discriminatory information can be spotted visually and then eliminated; problems in classification can be anticipated.

3. A simple two- or three-component image descriptor will perform as effectively as other more complex descriptors, such as LAWS or MAX-MIN texture.

4. The effectiveness of statistical classification methods and texture analysis is limited.

5. Processes that can guide the detection of textural patterns and aid in the decision-making process are needed.

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BIBLIOGRAPHY

Crombie, M.; Rand, R.; and Friend, N., Analysis of the Max-Min Texture Measure, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0280, January 1982, AD-A116 768.

Crombie, M.; Rand, R.; and Friend, N., Scene Classification Results Using the Max-Min Texture Measure, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0300, July 1982, AD-A123 496.

Crombie, M.; Friend, N.; and Rand, R., Feature Component Reduction Through Divergence Analysis, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0305, October 1982, AD-A123 474.

Friend, N., Analysis of Interactive Image Cleansing Via Raster Processing Techniques, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0347, November 1983, AD-A141 772.

Laws, K., Textured Image Segmentation, Image Processing Institute, (USCIPI Report 940), Univ. of Southern California, Los Angeles, CA, January 1980.

Rand, R., and Shine, J., Feature Analysis and Reduction of the Laws Texture Measure, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0343, October 1983, AD-A138 366.

Rice, W.; Shipman, J.; and Spieler, R., Interactive Digital Image Processing Investigation, prepared for U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0172, December 1978, AD-A076 342.

Rice, W.; Shipman, J.; and Spieler, R., Interactive Digital Image Processing Investigation, Phase II, prepared for U.S. Army Engineer Topographic Laboratories, Fort Belvoir, VA, ETL-0221, April 1980, AD-A087 518.

Rosenfield A.; Hummel R.; and Zucker S., "Scene Labeling by Relaxation Operations," IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-6, June 1976.

APPENDIX A. Laws Texture Data

Following a procedure suggested by Kenneth Laws,[13] 15 component vectors can be generated as texture data from gray-shade imagery. A three-step procedure is advocated. The first step is to convolve the desired image points with 16 different masks, resulting in a convolved image plane for each mask. The set of masks is defined by the cross-product computations of four five-component vectors:

$$L = (\ 1 \quad 4 \quad 6 \quad 4 \quad 1)$$

$$E = (-1 \quad -2 \quad 0 \quad 2 \quad 1)$$

$$S = (-1 \quad 0 \quad 2 \quad 0 \quad -1)$$

$$R = (\ 1 \quad -4 \quad 6 \quad -4 \quad 1)$$

The letters stand for level, edge, spot, and ripple. Multiplying one vector by a transpose of another (or the same) vector produces the sixteen 5X5 windows. When moved across all possible pixels on an MXN image, an (M-4)X(N-4) convolved image results; 16 windows produce 16 convolutions. Adding a border of two pixels to each side of the resultant image brings the image back to its original size.

In the second step, each point in the 16 convolved images is transformed to a measure of texture energy by a moving window operation that computes the standard deviation of the KXK points surrounding it (Laws used K=15). In the third step, the texture energy planes are ratioed to the first plane. The LXL^T window is used for normalization since its standard deviation values will be larger than any of the other 15 planes. Each of the other 15 planes is divided by the "LL" plane, resulting in 15 texture energy planes that have values between 0 and 1.

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